

Accepted Manuscript

Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts

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PII: S1045-926X(18)30100-9
DOI: <https://doi.org/10.1016/j.jvlc.2018.11.002>
Reference: YJVLC 868



To appear in: *Journal of Visual Languages and Computing*

Received date: 25 June 2018
Revised date: 22 August 2018
Accepted date: 13 November 2018

Please cite this article as: Gayane Sedrakyan , Erik Mannens , Katrien Verbert , Guiding the choice of learning dashboard visualizations: Linking dashboard design and data visualization concepts, *Journal of Visual Languages and Computing* (2018), doi: <https://doi.org/10.1016/j.jvlc.2018.11.002>

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Highlights

- little is known theoretically on the dashboard design principles
- earlier research links design and educational science concepts to design feedback
- we extend earlier research by linking dashboard design and visualization concepts
- general recommendations are derived to guide the choice of visual representations
- a case example is given showing visualizations per intended feedback / goal

We confirm that this manuscript has not been published elsewhere and is not under consideration by another journal. All authors have approved the manuscript and agree with its submission to Journal of Visual Languages and Computing.

This work was supported by Internal Funds of KU Leuven - PROFEELEARN PDM/16/044

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Abstract

Learning dashboards are known to improve decision-making by visualizing learning processes and helping to track where learning processes evolve as expected and where potential issues (may) occur. Despite the popularity of such dashboards, little is known theoretically on the design principles. Our earlier research reports on the gap between dashboards' design and learning science concepts, subsequently proposing a conceptual model that links dashboard design principles with learning process and feedback concepts. This paper extends our previous work by mapping the dashboard design and data/information visualization concepts. Based on a conceptual analysis and empirical evidence from earlier research, recommendations are proposed to guide the choice of visual representations of data in learning dashboards corresponding to the intended feedback typology.

1. Introduction

Advances in educational technologies have generated increased interest in previously non-feasible approaches to provide process-oriented feedback (Sedrakyan, 2016) in the form of learning dashboards. Examining how learners interact within virtual learning environments (i.e., with each other, instructors, the environment) provides opportunities to reveal where things are progressing well and where problems may possibly occur (Sedrakyan, Malmberg, Verbert, Järvelä & Kirschner, 2018). Using this information, feedback can be provided that can help teachers and learners enhance engagement and achievement (Gašević, Dawson, Rogers, & Gasevic, 2016). Such feedback is presented in the form of visualizations in teacher- and learner-oriented dashboards (Bodily & Verbert, 2017; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012; Hu, Lo, & Shih, 2014; Mottus, Graf, & Chen, 2015). Furthermore, visualizations are often the only reasonable approach to analyze data to gain knowledge about the underlying processes and relations (Lange, Schumann, Müller, & Krömker, 1995).

Despite the popularity and the proliferation of dashboard solution providers, little is known about their design aspects to support the choice of visualizations when developing such dashboards. As stated by Lange et al. (1995), deciding on the right visualization methods is not easy at all: the user must be an expert to generate an effective visualization which considers the goal in mind and renders the characteristics of the given data set. Otherwise, the produced visualizations can be misleading and, as a consequence, may lead to wrong conclusions. Furthermore, while the topic of visualizations is very popular in data science education, teaching visualizations rather targets how to make a chart before even thinking about whether it is appropriate (Stoltzman, 2017).

Our previous work reports on the gap between Learning Analytics Dashboard (LAD) design and learning science concepts (Sedrakyan, Järvelä & Kirschner, 2016), exploring the links between the typology of feedback relevant for different learning goals and dashboard design concepts. In addition, we have proposed a conceptual model that links dashboard design with learning process and feedback concepts (Sedrakyan, Malmberg, Verbert, Järvelä & Kirschner, 2018). This paper extends our previous work by further linking the dashboard design and visualization concepts. Based

on a conceptual analysis and empirical evidence, recommendations are proposed for the choice of visual representations of data for different learning goals and feedback.

Methodology-wise, the work builds on earlier work on data visualization paradigms. In particular, literature on scientific data visualization methodologies was considered as a starting point. In addition, the goal orientation approach has been considered, which assumes mapping the types of information that the visual representations convey with the intrinsic characteristics of data and aims for interpretation. Our work extends these studies with the specific scope of learning related information visualization in the context of LADs. In particular, the contribution of the work includes the mapping of visual representation properties with the general aims of dashboards derived from earlier literature as well as meta-level aims such as feedback typology, learning goals, learning process regulation, learning effectiveness, etc.

2. Methodology

As Kerlinger (1979) noted in the seventies of the previous century, theories present a systematic view of phenomena by specifying relations among variables using a set of interrelated constructs/variables, definitions, and propositions. A conceptual framework can guide research by providing a visual representation of theoretical constructs (and variables) of interest (Creswell, 1994). In this paper, we aim to derive a conceptual framework to guide the design and development of educational dashboard visualizations. We then visualize the derived concepts and their relationship through a conceptual map. We further illustrate the conceptual framework using a case example that includes several visualization examples per intended goals and data characteristics. Not many publications can be found in the context of visualization paradigms/frameworks. Towards developing a stronger theoretical basis for visualization in scientific computation, Robertson (1990) bases the methodology for scientific data visualizations on objectively distinguishing the types of information conveyed by various visual representations and matching these to the intrinsic characteristics of data and to aims for its interpretation. Our work follows this approach by presenting recommendations based on the mappings between learning process variables and visualizations as well as the aims for interpretation, i.e., intended goals (e.g., feedback typology) and data properties in the context of LADs. The mappings are presented in a tabular format that explicitly link the relationships between educational concepts, LADs designs, visual paradigms concepts, and possible visualizations based on the tasks/aims for visualizations.

3. Classification of LADs based on earlier studies

In this section, we provide a brief overview of learning dashboards based on earlier studies in terms of the objectives, stakeholders, as well as general trends and expectations for future LAD instruments.

There are numerous studies discussing the benefits of using dashboards in education for novel feedback opportunities that may enhance learning (e.g. Duval et al., 2012; Dyckhoff et al., 2012; Hu et al., 2014; Mottus et al., 2015; Verbert et al. 2013; Verbert et al. 2014; Bodily & Verbert, 2017). These studies can be further classified based on the *intended goals, stakeholders, feedback typology, data, and analytics approaches*. Among others, LADs aim to support improved retention or *engagement, increased social behavior or recommendations* of courses and resources (Bodily & Verbert, 2017), both for *individual* and *group* learning purposes (Upton & Kay, 2009).

3.1. Stakeholders, intended goals/interventions, data sources and analytics approaches

From the perspective of the potential users, Klerkx et al. (2017) distinguish the following stakeholders: learner, teacher, administrator, and researcher. Ifenthaler & Widanapathirana (2014) generalize the users into the following stakeholders: mega-level (governance), macro-level (institution), meso-level (curriculum, teacher/tutor), and micro-level (learner).

In terms of the intended goals of dashboards, most studies limit themselves to student *performance outcomes* through self-reflection, awareness, and self-assessment (Bodily & Verbert, 2017) positioning learners in comparison with teacher specified and/or peer performance. Several LADs deliver cognitive feedback in a limited context, such as mathematical problems or formal assessment of writing drafts (Ferguson et al., 2016). Based on earlier studies on LADs and tools introduced, Park & Jo (2015) provide an overview of existing LAD instruments for different user groups as follows: The intended goals of LADs for *teachers* include 1. to provide feedbacks on students' learning activities and performance; 2. to identify and treat students at-risk; and 3. to visualize the evolution of participant relationships within discussion forums. The intended goals of LADs for *students* include: 1. to improve retention and performance outcomes; and 2. to help students see how well they are contributing to the group to improve group-work. The intended goals of LADs that target *both teachers/students* include: 1. to keep track of learners' interaction in e-learning systems; 2. to provide a visualization of learning performance with a comparison of whole class/group; 3. to enable students' self-reflection and awareness of what and how they are doing; and 4. to promote reflection and awareness of their activity.

Relatively recent research also introduces the needs for considering learning goals and orientations, effectiveness, and efficiency of learning processes, and subsequently dashboard feedback design (Sedrakyan et al. 2018) that provides feedback mechanisms based on the links between learning analytics and learning science concepts. Such a LAD targets learners both at individual and group level to improve learning processes and outcomes, as well as teachers to also help adapting an instructional design (Sedrakyan et al., 2018).

From the perspective of the intended interventions based on learning analytics, Schumacher, & Ifenthaler (2018) classify the following types of feedback: *summative feedback* (understand learning habits, compare learning paths, analyze learning outcomes, and track progress towards goals); *real-time feedback* (receive automated interventions and scaffolds and take assessments including just-in-time feedback) and *predictive feedback* (optimize learning paths, adapt to recommendations, increase engagement, and increase success rates). Sedrakyan (2016) uses a concept of process-oriented feedback distinguished by two general types of feedback: *cognitive feedback* (e.g., targeting at understanding related issues) and *behavioral feedback* (e.g., targeting at procedural types of issues). The latter type of feedback is further exploited in the context of regulated learning (Sedrakyan, 2016; Sedrakyan et al., 2016; 2018).

With regard to data sources, learning analytics use static (e.g., stored in spreadsheets, text files, databases, etc.) and dynamic (i.e., moving data such as stream of data from sensors, social media, and a log file during a learning process that allows to observe patterns and changes over time to possibly adapt real-time) information about learners and learning environments allowing assessing, eliciting, and analyzing them for real-time modeling, prediction, and optimization of learning processes, learning environments, and educational decision-making (Ifenthaler, 2015). From the data analytics perspective, in addition to statistical and data mining approaches targeting summative and outcome-oriented data visualizations, Sedrakyan (2016) highlights the need for process/sequence analytics to consider the procedural aspects in learning processes.

In terms of data collection, most studies are limited to logs that address university settings (Schwendimann et al., 2016). In terms of analysis approach in the context of LADs feedback, data mining approaches prevail targeting performance visualization and outcome feedback ("How do I

perform?”). Such dashboards are in addition limited to summative representations without focusing on support mechanisms to facilitate their interpretation (Bodily & Verbert, 2017; Park & Jo, 2015). Recent research also introduces the concept of *process-oriented* feedback for a broader learning process context outside university settings (“How can I do better?”, e.g., by looking for inefficient procedural and sequential aspects of learning processes) based on *process analytics* approaches (Sedrakyan, 2016; Sedrakyan, Snoeck, & De Weerd, 2014; Sedrakyan, De Weerd, & Snoeck, 2016).

While most of learning analytics tools are making use of learner activities for different learning tasks or administrative data, recent research shows increased interest in observing learner activities outside the learning environments as learning processes are not limited to learning activities within a learning environment. For instance, Di Mitri et al. (2016) observe the levels of productivity, stress, challenge and the potential impact on learning. This is an emergent research area for LADs that also focuses on biofeedback perspectives that can be achieved based on physiological data analytics collected from wearable sensors¹ as well as dashboard feedback on emotions (Leony et al., 2017; Sedrakyan, Leony, Muñoz-Merino, Kloos, & Verbert, 2017). Other examples may include network analytics (e.g., understanding the influence of social networks, behavior of using devices/software, etc.), eye tracking analytics (e.g., observing the use of resources outside a learning environment and analyzing how those were integrated by a learner during a learning task completion), etc.

3.2. Other expectations

Besides the overall goals and expectations from LAD instruments discussed above, Schumacher & Ifenthaler (2018) also highlight the relevance of system expectations such as the *capability to allow a high degree of customization*. With the introduction of MOOCs, big data (analytics) related dimensions became relevant in the literature on learning dashboards. In addition, recent research shows increased interest in exploring biofeedback opportunities based on multi-modal data collected from various wearable sensors and audio/video streams. Thus, *scalability* is yet another requirement for learning analytics dashboards that use large volumes of (live) learner data (such as data from wearable sensors) collected from various sources in a variety of data formats.

3.3. Summary of LAD concepts

Table 1 shows an overview of LADs classification based on earlier studies discussed in this section.

Table 1 Overview of LADs classifications based on intended goals, stakeholders, data sources, and analytics approaches

Feedback *	awareness of learning process and progress
	support cognitive processes
	affect behavior
	outcome-oriented (e.g., achievement level)
	process-oriented (e.g., procedural information)
	summative (e.g., results, resource/time usage, etc.)
	real-time (immediate feedback during a learning process)
	predictive (e.g., identify failure risks)
Mega-level (governance)	support decision making in educational domain for optimization of the field, KPI visualization, benchmarking

¹ Strategic regulation of learning through Learning Analytics and Mobile clouds for individual and collaborative learning success (SLAM) project, funded by the Academy of Finland.

Stakeholders	Macro-level (institution, e.g., administrator, researcher)	identify issues and support decision making, optimization of learning processes, learning environments, and educational decision-making, analytics, feedback automation
	Meso-level (curriculum, teacher/tutor)	provide feedback on students' learning activities and performance
		help to identify (predict) and treat students at-risk
		visualize the evolution of participant relationships within discussion forums; group interactions
	Micro-level (learner)	improve retention and performance outcomes
		to help see how well they are contributing to the group to improve group-work
		to help adapting instructional design
	Combined (teacher & learners)	keep track of learners' interaction in e-learning systems
		provide a visualization of learning performance with a comparison of whole class/group
		to enable students' self-reflection and awareness of what and how they are doing
Data/analytics approaches		Summative representations based on statistics
		Sequential representations based on process analytics
		Predictive analytics based on machine learning or predictive models (feature engineering)
Data sources		Static (e.g., stored in spreadsheets, text files, databases, etc.)
		Dynamic (e.g., moving data such as stream of data from sensors, social media, a log file during a learning observe changes in behavior over time to possibly adapt real-time feedback/prediction models, etc.)
	Online (obtained from digital sources)	
	- Within learning environments	
	- Outside learning environments	
	Offline (obtained through non-digital sources, e.g., offline learning tasks, etc.)	
Other expectations		Multi-modal (video/audio/sensor streams, hybrid – combinations of multiple datasets that can be as well of heterogeneous origins)
		Scalability (e.g., relevant to MOOCs, big data obtained from sensors)
		High degree of customization (interactivity and adaptability to end-user preferences, searchability, zoom into different abstraction/granularity levels, etc.)

** the types of feedback are not mutually exclusive, e.g., awareness can be supported by summative, cognitive, process-oriented, real-time feedback, etc., while process-oriented feedback can use a combination of cognitive and behavioral feedback that may also be outcome-oriented for intermediate learning achievements to improve a final outcome*

In summary, LADs in earlier studies can be classified based on the intended goal (e.g., summative outcomes, real-time process-oriented feedback, and predictive), stakeholders (e.g., learners, teachers, administrators, researchers, etc.) classified into mega-, macro-, meso- and micro-level users, type of learning tasks (e.g., problem solving, solo, group learning, ...), feedback typology (cognitive and behavioral), data analytics characteristics (e.g., static/dynamic data with different level of dimensionality and aggregations analyzed by statistical, data mining, and process/sequence oriented techniques). As already mentioned, visualizations are often the only reasonable approach used to analyze and gain knowledge from various learning datasets about the underlying learning processes and relations. However, while recent research discusses the needs and ways of linking dashboard and learning science concepts to improve the accuracy and effectiveness of LAD solutions, to the best of our knowledge, there is no publication that provides theoretical support for the choice of visualization representations to guide their design and development process. Our work targets this specific gap by highlighting the meta-level links between dashboard design aspects (intended goal, stakeholders, type of learning tasks, feedback typology, data and analytics characteristics) and visualization concepts in the context of learning dashboards.

In this work, we will focus on the following subset of LAD properties:

- Learners (*individual* and *group*) and teachers as stakeholders;
- Feedback or needs for instructional design adaptation in the form of both outcome and process visualizations targeted to affect awareness, cognition, behavior;
- Learner data both inside/outside learning environments.

4. Educational science concepts relevant for dashboard feedback design

Recent research on dashboards also highlights several issues and trends for future solutions. For instance, research shows that while most dashboards and the feedback that they give are based only on learner performance indicators, effective feedback needs also to be grounded in the regulatory mechanisms underlying learning processes and awareness of the learner's learning goals (Sedrakyan, et al., 2018). Furthermore, recent research on the effectiveness of learning analytics tools reveals that when using performance-oriented dashboards, learner mastery orientation decreases (Lonn, Aguilar, & Teasley, 2015). This suggests that such goal orientations need to be carefully considered in the design of any intervention, as the resulting approaches and tools can affect students' interpretations of their data and subsequent academic success (Lonn et al., 2015). Earlier studies on learning dashboards highlight a number of dimensions that need to be considered when designing feedback dashboards. Sedrakyan et al. (2018) provide an overview of the concepts that need to be considered to support the links between dashboard design and educational sciences and allow effective observing of learning processes with respect to potential feedback needs of different learners for different learning goals, as well as for teachers to assess the needs for interventions or adaptations in instructional design. Different theories have attempted to explain the process of how people learn. While there is no complete agreement between these theories, most agree that learning may be explained by two basic approaches and their combinations: cognitive theories (i.e., cognitivism, which views the learning process as a step-by-step knowledge construction process) and behavioral theories (i.e., behaviorism, in which learning is defined as a change of the behavior of a learner by reinforcing some aspect of her behavior; Tomic, 1993). As learning is multifaceted, these approaches are often intertwined. For instance, in sociocognitive learning theory (Bransford, Brown, & Cocking, 2000), learners are acting as constructors of their knowledge by reinforcing themselves with goal-directed behavior, which can be referred to as a sequencing of cognitive and behavioral activities (regulated learning). In the context of feedback research, these approaches translate into two major forms that can also be combined: 1) *explanations* that target improving the cognitive dimensions of knowledge acquisition (e.g., understanding) and 2) *guidance* intended to influence a learner's behavior (e.g., engaging in a specific type of activity believed to be related to a successful learning path; Sedrakyan, 2016). Cognitive feedback gives information to learners about success or failure concerning the task at hand through prompts, cues, questions, etc., that help learners to reflect on the quality of the problem-solving process (e.g., reasoning, thinking, and understanding). This type of feedback aims to improve learners' understanding of intermediate solutions allowing them to engage in self-regulatory learning mechanisms (van Merriënboer & Kirschner, 2012).

4.1. Feedback and regulation of learning

Previous studies (Alvarez, Espasa, & Guasch, 2012; Guasch, Espasa, Alvarez, & Kirschner, 2011, 2013) identify different types of cognitive feedback, such as corrective, epistemic or suggestive feedback, and their combination. *Corrective feedback* provides comments to the learner about the adequacy of learners' work (e.g., "This is not correct. The correct answer is ..."). *Epistemic feedback* requests and/or stimulates explanations and/or clarifications in a critical way (e.g., "Do you think what you have written reflects what the author means in her study? Why do you think that X is an example of what the author is saying?"). *Suggestive feedback* (sometimes referred to as directive feedback) includes advice or directions to the learner on how to proceed and/or continue and invites

him or her to explore, expand, or improve what he or she has done (e.g., “Giving an instance or an example of your position at the end of your argument would make your point both clearer and stronger”). Of course, it is sometimes possible to combine them (e.g., epistemic and suggestive).

In contrast to cognitive feedback that is given in the context of learning tasks such as problem-solving, behavioral feedback targets a change in behavior. This type of feedback relates to learner goals and targets improved awareness of the learning progress and potential regulation needs during the learning process. In the context of dashboards, the role of this type of feedback is to inform a learner whether he or she is “on track on his or her road map.” This theory can be exploited in the context of self-regulated learning (Butler & Winne, 1995). The regulation of learning is a central topic in research on feedback, which is defined as a learner’s ability to monitor and evaluate his or her progress with respect to self-improvement needs in the process of achieving learning goals (Zimmerman, 2011). It is a goal-directed intentional and metacognitive activity in which learners take strategic control of their actions (behavior), thinking (cognitive), and beliefs (motivation, emotions) toward the completion of a task (Zimmerman & Schunk, 2011). Research has shown that successful learners use a repertoire of strategies to guide and enhance their learning process – cognitive, behavioral and motivational – toward completing academic tasks (Zimmerman & Schunk, 2011). In practice, self-regulated and strategic learning involves experimenting with, and learning about, effective strategies for regulating aspects of their own, peers’, and groups’ shared learning processes (Winne, Hadwin, & Perry, 2013), including planning, goal setting, organizing, monitoring, and adapting. This type of process can be referred to as a sequencing of cognitive and behavioral activities, suggesting that in terms of data analysis approaches, we also need to consider the role of process (sequence) analytics (Sedrakyan, 2016; Sedrakyan et al., 2014) as opposed to the statistical and data-mining approaches currently widely applied in research on learning analytics.

Although self-regulation concerns the individual behavior adaptation, feedback mechanisms that the environment or peers provide can also be considered as a form of co-regulated learning (Isohätälä, Järvenoja, & Järvelä, 2017). Co-regulated learning (CoRL) occurs when learners’ regulatory activities are guided, supported, shaped, or constrained by others, such as peers or teachers, and the social system, including the learning environment (Hadwin, Järvelä & Miller, 2017). CoRL can take at least two forms. In the first form, CoRL occurs when learners are prompted to set learning goals. In the second form, CoRL occurs when a social system gradually influences and shapes an individual’s SRL (e.g., when learning behavior is affected by comparing one’s own behavior with that of one’s peers). In the context of carrying out collaborative learning tasks, three types of regulation are posited to be required for achieving success: 1) self-regulated learning (SRL) in which group members take control of their own thinking, behavior, motivation, and emotion in the collaborative task, 2) co-regulated learning (CoRL) in which group members provide transitional support facilitating one another’s engagement in self-regulatory processes within the task, and 3) socially shared regulation of learning (SSRL) in which group members work together to regulate their cognition, behavior, motivation, and emotions together in a synchronized and productive manner (Hadwin et al., 2017; Järvelä & Hadwin, 2013).

Thus, tracking regulation patterns during a learning process can be helpful in determining possible intervention needs during a learning process (e.g., “Where is regulation effort needed? Is it sufficient? Is the expected outcome reached? Does the learner’s effort need to be redirected or does he or she need external help?”).

4.2. Learning goals and orientation

Different approaches can be distinguished in terms of the way people learn (i.e., set their learning goals), which is explained by the concept of *goal orientation*. Goal orientation has been found to affect learning behavior (Stevens & Gist, 1997). If goal orientation is aimed towards obtaining good grades, then this is seen as *performance orientation*. When goal orientation is aimed

towards becoming good or better at something, then this is seen as *mastery orientation*. Depending on the types of goals learners possess, learning outcomes will thus target different levels of knowledge, skills, competences, or simply task completion, which also determines how learners engage with the regulated learning process (Winne, Hadwin, & Perry, 2013). Students with mastery goals are typically interested in learning as an end itself (e.g., “One of my goals in class is to learn and understand as much as I can.”) while students with performance goals are typically interested in learning as means of demonstrating their ability or competence (e.g., “I want to do better than other students in my class”; Dweck & Leggett, 1988). Approach avoidance is another concept. When a negative, undesirable outcome is expected: the learner will have the desire to avoid failure. For instance, performance-avoidance oriented learners will be guided by *the desire to avoid performing poorer than others do*, while mastery-avoidance means striving to avoid performing worse than one aspires to.

4.3. Effectiveness and efficiency as means to measure a learning progress

Other important concepts in feedback dashboard design include the *effectiveness* and *efficiency* of learning which, complemented by the regulation effort, can help to assess a learning progress with respect to potential intervention needs and, more specifically, with respect to determining optimal “receive time”, i.e., *timeliness* of feedback by discovering inefficient or ineffective processes during learning (Sedrakyan et al., 2018). According to Frøkjær, Hertzum, & Hornbæk (2000), effectiveness is “the accuracy and completeness with which users achieve certain goals” (p. 345). The authors give a number of indicators of effectiveness, such as the quality of the solution and the number of errors. Regarding learning, it is more effective if the learner learns what he or she is aiming for, either more or better. Efficiency, on the other hand, “is the relation between 1) the accuracy and completeness with which users achieve certain goals and 2) the resources expended in achieving them” (Frøkjær et al., 2000, p. 345). The authors also give a number of indicators of efficiency, such as the time it takes to complete a task and the time it takes to learn what is aimed for. These concepts can use measurement approximations such as (intermediate) outcomes of task specific sub-goals, learning resources, and the allocation of expected timeframe for achieving a learning (sub-)goal. Tracking the utility of the learning material can inform a learner/teacher if a learner effectively makes use of a learning resource defined for a specific goal. For example, if the expected utility of a specific resource within a meaningful (agreed) time does not lead to the achievement of the expected learning goal, either for a specific learner or group of learners (depending on the observation target), it might suggest that the resource for a specific goal contains a certain level of “difficulty” for that cluster, and vice versa (“too easy”).

4.3.1. Instructional design enabled effort approximation

Most learning is an individual mental activity, such as the actual process of thinking, reasoning, reflecting, and so on. Thus, the traceability of the above discussed concepts in this section constitute yet another important dimension for dashboard design. Sedrakyan et al. (2018) suggest that effective approximations of learners’ efforts need to be defined based on their behavioral traces within a learning environment. These approximations will allow the measurement of learning progress with respect to learning goals (Winne et al., 2006). From a self-regulated learning perspective, goals provide learners with standards against which they can monitor the learning process and progress. Sedrakyan et al. (2018) propose the concept of *Task-specific sub-goals* (TSSG), as they include steps that are 1) specific, 2) measurable, 3) action-oriented, 4) realistic, and 5) temporal (Winne & Hadwin, 1998). To that extent, they are visible markers of learners SRL at different points in time. TSSGs can be defined both by learners and instructors. For example, “*backward design*,” which is a well-known instructional design model, uses goal setting as the focal point of lesson design (Wiggins & McTighe, 1998). When using backward design, instructors identify learning goals for the course first, considering what they want students to know, and be able to do

when they finish the course, and then determine acceptable evidence regarding whether those goals are met. Then, they plan learning experiences and instructions to achieve those learning goals (Wiggins & McTighe, 1998). A simple form of a TSSG can include reading course material, engaging in exercises, and the successful completion of tasks, such as online tests. That is, by creating visible artefacts of varying sub-goals related to mastering the new knowledge or skills and/or competence, we can make them observable in the learning process for both the instructor and learner. Thus, both the instructor and learner can define concrete TSSGs that need to be achieved. TSSGs can be defined when, for instance, planning learning processes and achievements. To enable dashboard feedback based on TSSGs, we create the premise that they are initially carefully defined by an instructor in the context of instruction design and in accordance with goal-setting theory.

4.4. Emotions and affective states

Yet another relevant topic in research on learning processes is concerned with emotions. The interplay between learning and emotions has been recognized in many studies (Kort, Reilly, & Picard, 2001; Trigwell, Ellis, & Han, 2012). Recent research has highlighted the importance of supporting awareness of these emotions (Ashkanasy, & Dasborough, 2003). For example, students can reflect about the type of emotions they felt, the activities that generated certain emotions or their evolution over time. By analyzing their emotions, students can take decisions to improve their learning process, based, for instance, on information from studies that relate learning outcomes with affective states (e.g., Baker, D'Mello, Rodrigo, & Graesser, 2010).

4.5. Summary of educational science related concepts in the context of LADs

Table 2 shows an overview of educational science concepts based on earlier studies on LADs discussed in this section.

Table 2 Overview of learning science concepts relevant for dashboard design based on Sedrakyan, 2016; Sedrakyan et al., 2018.

Concept	Sub-categories / related concepts		Linked LAD concepts
Feedback*	Cognitive	Corrective feedback	outcomes of TSSGs
		Epistemic	outcomes of TSSGs
		Suggestive feedback (sometimes referred to as directive feedback)	learning goals, dependencies, (intermediate) outcomes of TSSGs or outcomes of intermediate TSSGs
	Behavioral	procedural or cognitive, outcome-oriented feedback on intermediate outcomes	learning goals, dependencies, (intermediate) outcomes of TSSGs or outcomes of intermediate TSSGs
	Outcome-oriented	Cognitive/behavioral feedback on learning outcomes	outcomes of TSSGs
Regulated learning	Self-regulation	Process-oriented	(intermediate) outcomes of TSSGs or outcomes of intermediate TSSGs
		Self-oriented planning	Self-oriented profile
		Self-oriented monitoring	Self-oriented monitoring profile
		Self-oriented adapting	Self-oriented adaptation profile
	Co-regulation	Peer-oriented planning	Peer-oriented planning profile
		Peer-oriented monitoring	Peer-oriented monitoring profile
		Peer-oriented adapting	Peer-oriented adaptation profile
	Socially shared regulation	Group-oriented planning	Group-oriented planning profile
		Group-oriented monitoring	Group-oriented monitoring profile
		Group-oriented adapting	Group-oriented adaptation profile

Goal orientation	<i>Performance-orientation</i>	<i>Self-, Co-, Socially shared regulation</i>	<i>Self-/Peer-oriented planning profile, Self-/Peer performance on TSSGs</i>
	<i>Mastery-orientation</i>	<i>Self-regulation</i>	<i>Self-oriented planning profile, own performance on TSSGs</i>
	<i>Performance approach avoidance</i>	<i>Self-, Co-, Socially shared regulation</i>	<i>Self-/Peer-oriented planning profile, Self-/Peer performance on TSSGs</i>
	<i>Mastery approach avoidance</i>	<i>Self-regulation</i>	<i>Self-oriented planning profile, own performance on TSSGs</i>
Effectiveness of learning	<i>Accuracy</i>		<i>outcomes of TSSGs or outcomes of intermediate TSSGs</i>
	<i>Completeness</i>		<i>outcomes of TSSGs or outcomes of intermediate TSSGs</i>
Efficiency of learning	<i>Effort</i>		<i>resources, time spent on TSSGs</i>
User preference	<i>User assessment</i>		<i>User feedback</i>
	<i>User control</i>		<i>Interactivity</i>
Emotion regulation	<i>Support for awareness affective states</i>		<i>affect intensity for a TSSG/timeframe, compared with those of peers</i>

** the types of feedback are not mutually exclusive, e.g., behavioral feedback can be supported by cognitive feedback to intermediate results, process-oriented feedback can use a combination of cognitive and behavioral feedback that may also be outcome-oriented, outcome-oriented feedback can take a form of cognitive feedback to a learning task outcome, process-oriented feedback can use outcome-feedback to intermediate outcomes of a learning task, etc.*

In summary the following concepts have been chosen to be considered for further conceptual mappings in the next section.

- Type of feedback such as cognitive/behavioral in the context of outcome/process-oriented guidance;
- Learning regulation measured by planning (goal setting), monitoring, adaptation to be supported by self-, peer-, group-oriented feedback in the context of self-, co-, socially shared regulation of learning;
- Type of learning goals such as performance/mastery;
- Type of goal orientations such as approach/avoidance;
- Effectiveness/efficiency of learning measured by the (intermediate) outcomes and time/resources spent;
- Emotion regulation aspects by means of supporting awareness for affective states.

Sedrakyan et al. (2018) also propose the concept of user control to allow both teachers and learners to specify preferences such as receive time, level of detail, etc. The authors also propose built-in assessment mechanisms to continuously adapt LADs feedback to user expectations.

5. Visualization and design paradigms, classification of properties and aims for interpretation: in which case and for what reasons do you need a visualization?

In this section, we provide a brief overview of visual frameworks/paradigms to understand what are the potential implications when mapping with learning data representations and objectives in the subsequent sections.

5.1. Visualization metrics

Advances in computing technology and graphics have introduced a plentitude of techniques for visual representations of data. While this offers a large choice of visualization techniques to allow users to gain insights from large datasets, still the choice of the most suitable visualization for a given dataset, the task to be performed and the aims for interpretation are subjective. There have been many research studies on theoretical frameworks to guide visualization choices for various dataset domains. These studies propose various classifications and characteristics to be considered in general when producing visual representations. Halim & Muhammad (2017) for example introduce a set of visualization metrics to quantify visualization techniques. Based on a comprehensive literature survey, they propose *effectiveness*, *expressiveness*, *readability*, and *interactivity* as the visualization metrics.

5.2. Taxonomies and intrinsic characteristics of data

In another approach, the intrinsic characteristics of the dataset at hand are used as a primary directive for the choice of visualizations. For instance, Dastani (2012) proposes an effective data visualization process model based on which data needs to be structured in a way that will allow further structural mappings with perceptual structures and ultimately with the interpretation goals. In this model, the effectiveness of visualization is defined as follows: a visualization presents the input data effectively if the intended structure of the data and the perceptual structure of the visualization coincide. The *dimensionality* of data in the model is highlighted as a relevant structural property of the data which is achieved by structuring data into attributes ensuring relevant relationship representations, which in turn will be projected into connections with perceptual structure attributes. The *structural attributes* are further classified as discontinuous (nominal, ordinal), continuous (intervals, ratios), aggregated, etc.

Furthermore, based on an extensive overview of different visualization techniques Verbert and Bordalejo (2018) provide a classification of the choice of data visualizations by data type taxonomies as well as based on the type of relationships in the data to be visualized.

5.2.1. Data types, structures and tasks

Schneiderman (2003) proposes the concept of interactive visualization in the framework called information visualization seeking mantra. This mantra insightfully summarizes the essential elements of interacting with graphically presented information proposing the “Overview first, zoom and filter, then details-on-demand”. The approach is summarized with the following tasks:

- Overview: gain an overview of the entire collection, e.g., high-level information with contextual data, features allowing to query, navigate, etc.
- Zoom: zoom in on items of interest (example of visual enabler may include a pointer for any point of interest to request detailed views or a specific dimension)
- Filter: filter out interesting items (examples of visual enablers may include a drag and drop, checkbox, range sliders, more advanced features may support dynamic query interfaces allowing to answer a specific question using conjunction/disjunction, Boolean, negation operations, etc.)
- Details-on-demand: select an item and groups and get details when needed (e.g., click on an item and retrieval of specific values in a popup window as an outcome)
- Relate: view relationships among them (e.g., select an item to highlight related other items, or items with similar attribute, e.g., selecting a name of director from a list of filmmakers to highlight all films by that director, etc.)

- History: keep a history of actions to support undo, replay, and progressive refinement (e.g., a graphic interface allowing to see all previous searches by a user, etc.)
- Extract: allow extraction of sub-collections and of the query parameters (e.g., ability to save the desired item or a set of items in a format that facilitates further needs such as printing, sending, graphing, or inserting into statistical package, etc.)

Further follows the description of seven data types that can guide the visualization choice according to Schneiderman (2003):

- Dimensionality:
 - o one-dimensional: linear data types including textual documents, program codes, lists of names (string of characters), organized in sequential manners, where interface features include size, font, color, and overview task for selection, e.g., through scrollbars and focus area;
 - o two-dimensional: planar or map data (e.g., geographic maps) that imply interface features such as size, color, opacity, and tasks of counting and filtering details on demand;
 - o three-dimensional: real world objects that have volumes, e.g., human body or buildings, that have potential complex relationships, where interface features include computer graphics, and overview task for landmark, perspective, position display, etc.;
 - o multi-dimensional: most relational and statistical databases, where tasks include finding patterns, clusters, correlations among pairs of variables, and interface features include selective dynamic manipulations with aggregations, movable filters, etc., that may use various visual representations (e.g., linked histograms, scattercharts, etc.);
- temporal: time lines with start and finish time that may overlap, where frequent tasks include finding an event before, after, during some time period or moment in patient history, video stream, etc. that may use various visual representations;
- tree: hierarchical structures that have links to one parent (except the root), e.g., file directories, sales data, etc., with multiple attributes for relations between parent and child, where tasks may include finding a parent, child node, and levels in the structure, etc., and interface representations can include node, link diagrams, or treemaps;
- network: linked arbitrary number of items relations that can be, e.g., acyclic, (un)directed, ... that cannot be conveniently captured with a tree structure, and where usual tasks may include finding a shortest or least costly path among items, traversing entire network, etc. usual visualizations here may include a node or link diagram or square matrix having link attributes.

5.3. Objectives and reasons of visualizations

Munzner (2014) suggests classifying the reasons for visualizations such as *explore*, *discover*, *summarize*, *present*, and *enjoy* among others.

Stoltzman (2018) gives a classification of visualizations per aims: 1) *Comparison*; 2) *Relationship*; 3) *Distribution*; 4) *Trend over time*; and 5) *Composition*. Visualizations according to Stoltzman (2018) can be classified as:

- *Good visualizations* – 1) clearly illustrate a point; 2) are tailored to the appropriate audience, e.g., analysts may want detail while executives may want a high-level view; 3) are tailored to the presentation medium, e.g., an article in an academic journal may need to be analyzed

carefully, while a slide in front of 5,000 people in a conference will be glanced at quickly; and 4) are memorable to those who care about the material and make an impact which increases the understanding of the subject matter;

- *Bad visualizations* – 1) are difficult to interpret; 2) are unintentionally misleading; and 3) contain redundant and boring information;
- *Ugly visualizations* – 1) are almost impossible to interpret; 2) are filled with completely worthless information; 3) are intentionally created to mislead the audience; and 4) are inaccurate.

Stoltzman (2017) further advises that “If all of the above criteria classified under ‘good visualization’ do not seem possible, *you probably don’t need a data visualization*”.

In terms of pure visual representations, Stoltzman (2018) recommends focusing on the outcomes, i.e., aims of visual representations (comparison, relationship, distribution, trend over time, and composition) to help narrow down the charting options. As a general rule of thumb, the author classifies the following minimal set of mappings in terms of intended goals and possible relevant visualizations:

- Trend: Column or Line
- Comparison: Area, Bar, Bullet, Column, Line, or Scatter
- Relationship: Line or Scatter
- Distribution: Bar, Boxplot, or Column
- Composition: Donut, Pie, Stacked Bar, or Stacked Column

5.4. Summary of data visualization concepts

Table 3 shows an overview of data visualization concepts based on earlier studies on visualization and interaction concepts discussed in this section.

Table 3 Overview of data visualization, design and interaction paradigm concepts

Visualization metrics	Effectiveness	
	Expressiveness	
	Readability	
	Interactivity	
Data characteristics	Structural attributes	discontinuous (nominal, ordinal, or categorical) continuous (intervals, ratios)
	Tasks	overview
		zoom
		filter
		details-on-demand
		relate
		extract
	Data types	dimensional (one-, two-, three-, or multi-dimensional)
		temporal
		tree
		network
Visualization objectives	Comparison	
	Relationship	
	Distribution	
	Trend over time	
	Composition	
Reasons of visualizations	Explore	
	Discover	

Relevance	<i>Summarize</i>
	<i>Present</i>
	<i>Enjoy</i>
	<i>Has a clear goal (WHY)</i>
	<i>clearly illustrates the point: conveys the intended information with relevant level of detail, does not contain redundant/irrelevant information (WHAT)</i>
	<i>adapted to intended audience (WHO) and presentation medium</i>
	<i>are memorable to those who care about the material</i>
	<i>makes an impact which increases the understanding of the subject matter</i>
	<i>uses appropriate representation to visualize data (HOW)</i>

In summary, the following concepts have been chosen to be considered for further conceptual mappings in the next section:

- Aims of visualization: comparison, relationship, distribution, trend over time, and composition;
- Reasons of visualization: explore, discover, summarize, present, and enjoy;
- Relevance of information and level of detail: tailoring to appropriate audience, i.e., learners and teachers;
- Data characteristics such as dimensionality and structural properties, such as continuity, intervals, and aggregations/ratios;
- Types of charts per aims of visualizations;
- Other visualization metrics: effectiveness, expressiveness, readability, and interactivity.

For some cases, mixed representations may be needed, e.g., not only comparisons across values but also trends over time, granular distributions/compositions across certain relationships, etc. (see examples in Section 6 on mapping the discussed concepts with visual representations). As already stated in the methodology section, the work will further focus on the types of information conveyed by various visual representations and matching them to the intrinsic characteristics of data and to the aims for interpretation, i.e., the learning goals and intended feedback. The visualization metrics and structure attributes discussed in this section are to be taken into account for further conceptual level mappings.

6. Mapping learning science concepts with visual representation properties and aims for interpretation in the context of feedback dashboards

In this section, we provide recommendations for the choice of visual representations based on the links between learning process and feedback related concepts with the visualization concepts discussed in previous sections. This section is a summary of feedback examples based on the visualization techniques used in earlier empirical studies that demonstrate the effectiveness of the techniques in different learning contexts. For each case, a link with data/analytics and intended feedback typology is clarified. Subsequently, a set of guidelines are derived to support the choice of visualizations in the context of LADs. It has to be noted that visualizations, that aim scientific analysis purposes (e.g., to observe normality of distributions, machine learning, predictive models, etc.) that are more researcher-oriented, are beyond the scope of this work. The visualizations discussed in this section are to support the goals for two types of users discussed in earlier sections (e.g., behavioral/cognitive process-oriented feedback to support awareness of learning processes and progress according to learner/teacher specified goals). We first present a case example of LADs

visualizations from a learner perspective. Then, we elaborate on LADs visualizations from a teacher perspective.

6.1. Learner perspective

When mapping learning analytics and learning science concepts, Sedrakyan et al. (2018) suggest profiles that aim to facilitate the visual representations for regulatory sub-processes of learning. For instance, a planning profile allows to visually represent learning goals and activity plan, and guides learners about the coherence and alignment between learners' and teacher's specified goals and action plans. In general, a planning profile includes activities such as 1) planning the sub-goals to reach; 2) selection of learning strategy (action plan); 3) the materials and resources to use; and 4) allocation of time (Pintrich, 2000). In the planning phase, using backward design, the task specific sub-goals necessary to obtain knowledge or a skill are linked with mastering the proposed learning material. This means that the actual use of learning resources can to a certain extent be indicative of learning outcomes. Examples of learning resources include instructor's uploads into a learning environment (e.g., lecture slides, URLs for extra reading material, video lectures, exercises, homework, tasks, and tests) for obtaining specified knowledge or skills, which in turn are a pre-requisite for the next learning level. These resources can serve as artefacts of instructor expectations or planning. Likewise, a learner can choose his or her (sub/super)set of different learning goals. A planning profile should allow a learner to 1) "interact with a teacher view" with a goal to "consult the teacher view" regarding defined goals and trajectories for learning; 2) add his or her own (sub-)goals and link them to (sub-)goals, tasks, and resources within and outside the learning environment; and 3) indicate preferences ("I want to perform equally to my peers") and receive self-oriented feedback that helps him or her construct an optimal learning path (action plan) to reflect on the quality and completeness by checking the needs for completion of prerequisite goals and tasks.

In general, such planning profiles should allow *interactive choices of learning goals* and reflect on a *sequential visualization in such a way that a trajectory of steps (sub-goals, sub-tasks) along with pre-requisite goals can be followed*. Such trajectory visualizations should in addition allow interactive zooming into specific needs for each step (e.g., required learning resources, time to be dedicated, and tasks to be completed) with historic views (e.g., tracking progress by showing attempts for each task and achievements with each attempt) to allow tracking the effectiveness of the resources and intermediate feedback. In this specific case, the action plan shows the dependencies on other subgoals (e.g., pre-requisites for each subgoal) required to achieve the chosen goal and the measurements (TSSGs) and presentation layer concepts (planning profile) as proposed by Sedrakyan et al. (2018). The trajectory visualization should also allow showing the expected level of performance, coverage of what has already been achieved, and what the learner still needs to achieve towards her specified learning goal.

The profile utilizes the concept of self-oriented behavioral feedback discussed in earlier sections to guide the learner regarding the actions he or she needs to complete to reach a specific learning goal (Sedrakyan et al., 2018).

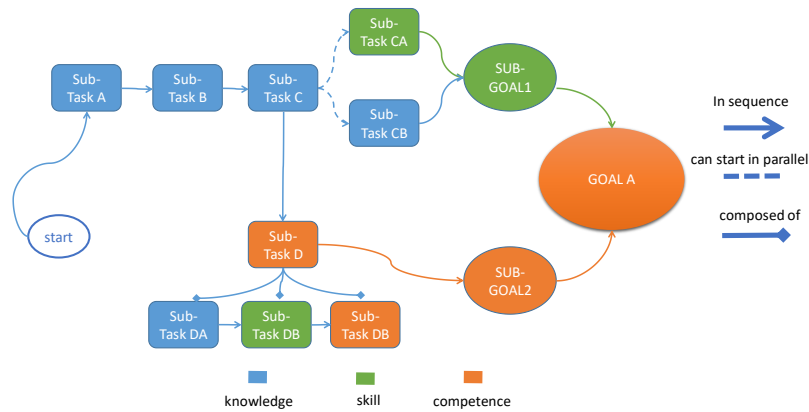


Figure 1. Based on a choice of a learning goal, a sample interactive learning trajectory is visualized representing a sequence of pre-/post- sub-goals within a planning profile (different goal levels modeled as knowledge, skill, and competence).

In summary, a planning phase can be realized through a *sequential representation* allowing to show a trajectory of learning steps towards a predefined learning goal as a sequence of TSSGs. Mastery/Performance orientation can be differentiated with the coloring scheme. The visualization should allow interactive choices for the goal orientation too. Similarly, a high-level recommendation on the choice of the courses/programs based on pre-requisite knowledge can utilize sequential visualizations to highlight the motivation of certain choices/recommendations.

Furthermore, the visual representations should allow a learner/teacher to zoom into the TSSGs with *comparison visualizations* to compare actual and required outcomes throughout the learning process in general as well as for certain timeframes of choice. Bar-charts are visualization techniques (e.g., Figure 2) to show a relationship between a part and a whole or compare categories, thus allowing to compare the planned and actual achievements during a learning process (e.g., online tests to measure learning goal outcomes). Area-charts and line-charts can emphasize the magnitude of change over time and draw attention to trends, e.g., intermediate results, such as homework and lectures (e.g., Figure 4 and Figure 5). The effectiveness of these techniques in quantifying achievement levels and supporting progress awareness has been shown in different learning contexts (Charleer, Klerkx, Duval, Laet, & Verbert, 2017). This type of visualizations intend to stimulate a monitoring behavior in LADs. From a regulated learning point of view, metacognitive monitoring enables learners to adjust or change their goals, plans, or strategies for learning. As suggested by Sedrakyan et al. (2018), monitoring profiles are presentation layer concepts that should visualize the engagement effort with respect to action plans (generated and/or recommended learning paths based on task-specific goals and their connections, such as prerequisite goals). Monitoring profiles should suggest comparative overviews to provide information about learners' progress with respect to defined goals and effectiveness and efficiency of learning. A self-monitoring profile can inform a learner about his or her progress with respect to an action plan and self-defined goals. A co-monitoring profile will allow the provision of peer-oriented feedback (e.g., "You seem to be efficient at completing this task. Can you give advice to your peer who seems to have difficulty with concept X?"). A co-monitoring profile can also provide information about how well a learner performs with respect to his or her peers if the goal orientation is set to "performance".

In general, the role of a monitoring profile in the context of dashboards is to keep track of learning progress towards the learning goals and detect/suggest further adaptation needs for learners and inform teachers about difficulties if the expected performance level is not being achieved within an agreed action plan and timeframe.

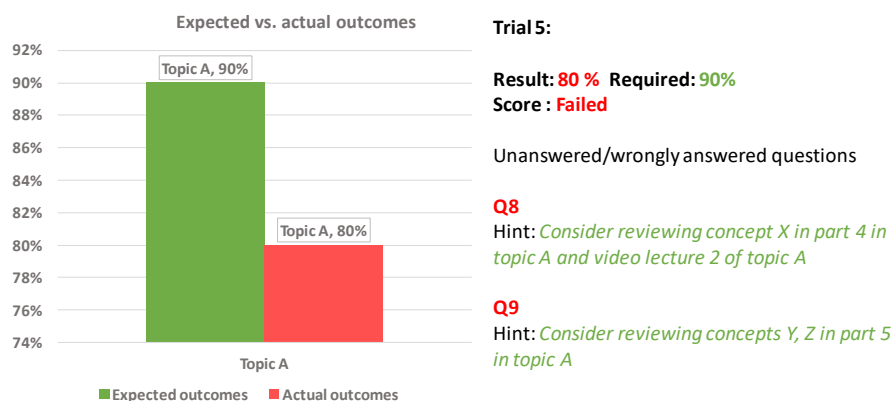


Figure 2. Sample comparative visualization in a monitoring profile showing a learner outcome contrasted with planned performance on a goal-specific task. The visualization is also enhanced with suggestive/corrective feedback (Sedrakyan & Snoeck, 2012).

Figure 2 shows an example of monitoring feedback (Sedrakyan & Snoeck, 2012). The profile informs a learner that his or her learning outcomes do not match the expected or planned performance to accomplish a goal-specific task (online test for topic A). The profile also includes cognitive suggestive or corrective feedback for improving (for two failed questions in this case) the effectiveness of which has been empirically tested in a learning context (Sedrakyan, & Snoeck, 2012). A bar-chart visualization technique can be recommended to support progress awareness by comparing the actual and required achievement levels.

Adaptation profiles (Sedrakyan et al., 2018) can inform learners about the level of effort put into learning regulation and the needs for adaptation (e.g., how learners perform with learning challenges, the resources they use, how much time they spend, and whether they need additional feedback). These profiles can make use of learner behavior following her viewing and monitoring activities to show approximations of adaptation effort. For instance, an increased or decreased effort in combination with achievements (e.g., score) can be indicative of whether activities, such as attending classes, use of a learning resource, task completion, or received feedback had an impact on achievements.

A self-adaptation profile is a representation layer concept (Sedrakyan et al., 2018): the goal is to inform a learner about how successful he or she was in addressing a challenge and what actions he or she can take to address a detected challenge. A co-adaptation profile (Sedrakyan et al., 2018) utilizes the concept of peer-oriented feedback (e.g., a comparative overview with peers, or a direct feedback request “Could you give feedback on your peer task results?”) both for individual and group learning plans. Data-wise these profiles need a historic view, e.g., different attempts for a same task need to be logged in the data store. Summative representations can be used to provide outcome-oriented cognitive feedback, and the concept of process-oriented feedback can be exploited by the use summative outcome representations of intermediate outcomes.

Figure 3 shows an example of an adaptation profile visualization (Sedrakyan et al., 2018) using the observations of learner engagement in goal-specific task completion and subsequent corrective trials (adaptations). The example shows that a learner successfully regulated his or her learning process by engaging in multiple trials of the same goal-specific task (behavioral self-oriented feedback). For each trial the use of intermediate cognitive suggestive feedback can be used (see for example Figure 2) to stimulate engagement and increased performance in another trial.

In summary, an adaptation profile makes use of contrast/comparative visualizations combined with the magnitude of change over time, i.e., trends.

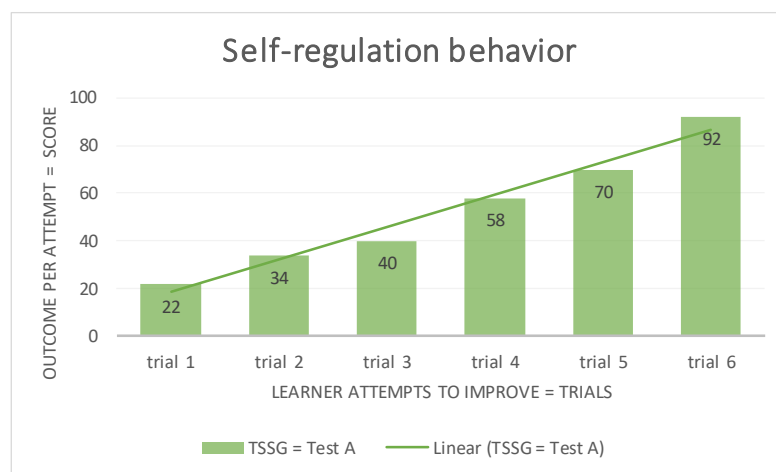


Figure 3. Sample adaptation profile visualization showing the magnitude of change (trends) over time based on comparative overview of attempts/outcomes for the same task (Sedrakyan et al., 2018). In this case, the visualization reflects a self-regulation behavior and a positive trendline.

Sedrakyan et al. (2018) complement the concept of adaptation profile by textual feedback on the effectiveness/efficiency of learning processes based on the intermediate use of time/resources in between the trials. Such visualizations can be used to provide self-oriented feedback to a learner as well as support a teacher to reflect on potential relevance/difficulty of the suggested learning resources for TSSGs both for individual as well as group learning processes.

Aggregated analysis with respect to peer performance has been proposed to be a suitable approach to exploit the concept of social influence (Lonn et al., 2015). Social influence has been observed to play an important role in students' motivations (Gruzd, Staves, & Wilk, 2012). Figure 4 shows a sample peer-oriented feedback (Sedrakyan et al., 2018) that visualizes the coverage of achievements, e.g., utility of learning resources and subsequent goal completion.

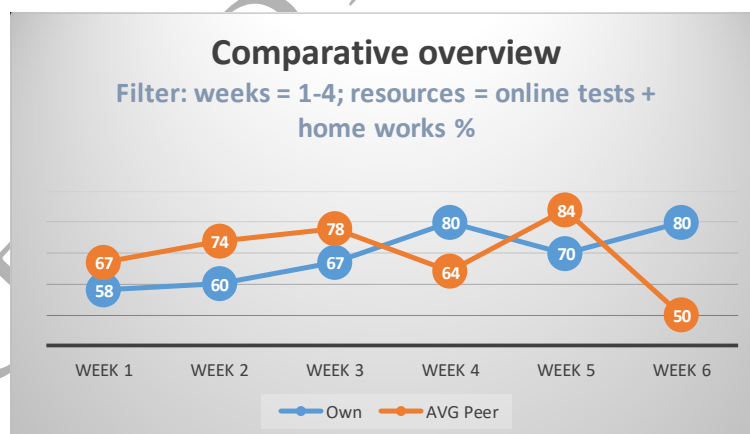


Figure 4. Sample visualization for contrasting actual and required performance on learning task specific sub-goals using line-charts.

Such visualizations can suggest for a given timeframe, whether a learner performs lower/equal/better than his or her peers for the same goal-specific tasks. Such a performance-oriented feedback visualization (Sedrakyan et al., 2018) is suggested to regulate learning processes for learners who lack sufficient motivation for goal setting and/or are highly performance oriented (the desire to outperform others) or performance-avoidance oriented (*the desire to avoid performing poorer than others do*). Similarly, a self-oriented feedback can be visualized contrasting the actual and planned (by a teacher or a learner) achievements.

Line-charts visualization can be recommended to support awareness of progress during specified periods of time. The line-chart is known to convey changes for multiple datasets over time by connecting data along an interval scale, which will show how data changes at equal intervals of time. Typically, the y-axis represents the dependent variable (test results in this example) and the x-axis represents the independent variable (time interval in this example).

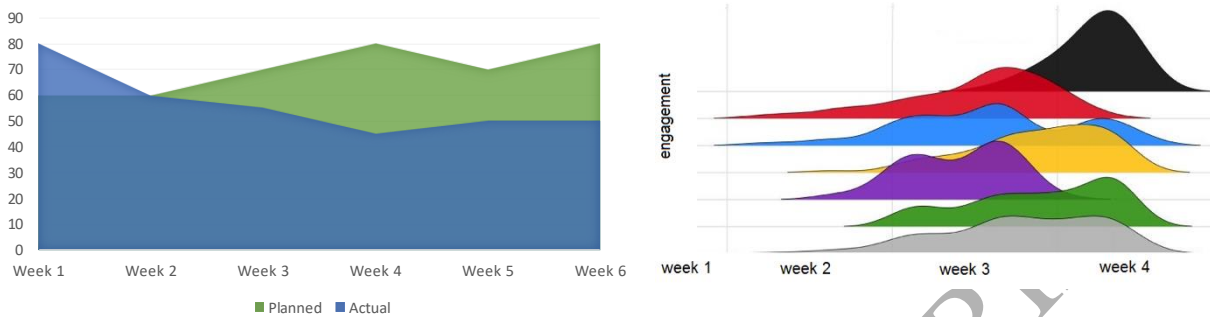


Figure 5. Sample comparison visualization to compare actual with planned performance (self-oriented feedback) or peer performance (peer-oriented feedback) on the left. Comparison for multiple learners' engagement (measured by volumes of resource utility) with ridgelines (joyplots) on the right.

Area-charts help to highlight the coverage, i.e., part-to-whole relationship, along with the time trends. This visualization technique can be used for comparative analysis of the actual achievements with either own planned or peer performance (e.g., see Figure 5). To avoid overlaps in comparative views, especially for multiple datasets, transparent coloring can be recommended.

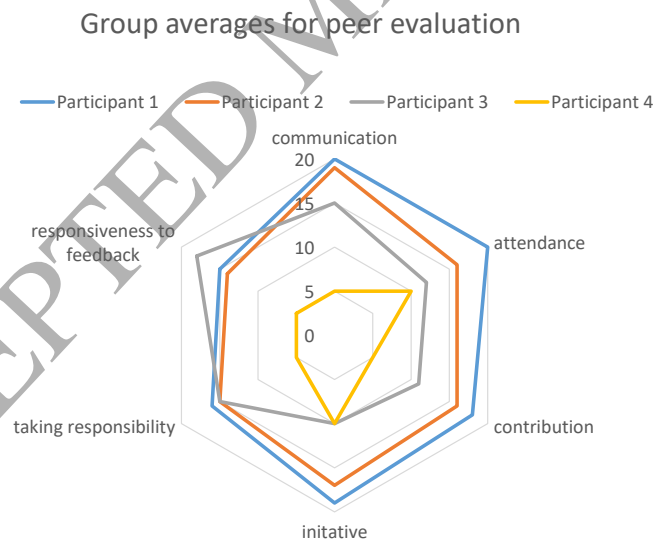


Figure 6. Sample group-oriented feedback by means of contrasted expectations of group members toward each other (Sedrakyan et al., 2018).

To provide group-oriented feedback, Sedrakyan et al. (2018) suggest to use group standards by visualizing contrasted evaluations of peers for the expected performance for shared tasks and/or shared standards for collaboration, as shown in Figure 6. Earlier research has demonstrated evidence of the effectiveness of such peer-oriented feedback mechanisms, and the use of radar chart visualization in particular, revealing more convergence between self and peer assessments, and reporting higher social group performance compared with groups that do not use such an approach

(Charleer, Klerkx, Duval, Laet, & Verbert, 2017; Leony, Sedrakyan, Munoz-Merino, Delgado Kloos, & Verbert, 2017; Ochoa et al., 2018; Phielix, Prins, & Kirschner, 2010; Phielix, Prins, Kirschner, Erkens, & Jaspers, 2011).



Figure 7. Sample visualization based on the concept of enjoyability (Santos, Charleer, Parra, Klerkx, Duval, & Verbert, 2013).

Figure 7 shows an example of visualization that is grounded on the concept of enjoyability. Santos et al. (2013) present a dashboard that aims to support awareness of students about their learning progress by abstracting student learning activities in the form of learning badges they have/can earn. The visualization represents different badges with icons and user color cues to indicate which badges have been earned. Gray badges have not yet been earned. Next to each badge a learner can explore how many of his/her peers have earned specific badges. Such fun elements can be applied in various learning context to stimulate learning achievement and behavior, e.g., interactions/discussions within collaborative tasks such as negative/positive attitudes, participation level, etc.

6.2. Teacher perspective

In addition to observing individual learning processes, the teacher perspective often needs group/class level performance such as comparative overviews, averages, etc. to analyze overall trends. The teacher perspective thus normally uses multi-perspective data to show aggregated representations. For example, observing engagement behavior measured by the amount of used learning resources and distribution over time may require a different approach than comparing two datasets of actual vs. planned or vs. class performance. Figure 5 shows an example of engagement behavior of a group of learners, measured by a volume of interactions within a learning environment over a specified 4-weeks period of time is contrasted.

Martin & Ndoye (2016) use a bubble chart to show a high-level representation of engagement for different students measured by a frequency of access to a specific learning module (see

Figure 8). While such a graph does not provide the exact distributions, it can be effective for the purpose of having a quick glance and getting a high-level overview.



Figure 8. Sample comparison visualization to compare engagement behavior of multiple learners in a specific module measured by the frequency of access. The higher the frequency of access, the bigger the circle size (Martin & Ndoye, 2016).

To observe a more detailed process view, a dotted chart technique can be recommended. Sedrakyan et al. (2014) used the technique to observe the differences of learner engagement measured by frequencies of interactions and gaps between engagement sessions over a semester (see Figure 9). In this specific case, a teacher might discover that while both better (denoted with “B” on the vertical axis) and worse (denoted with “W” on the vertical axis) performing learners were sensitive to deadlines (represented as vertical blue lines), learners with better outcomes demonstrated a more systematic engagement behavior in between the deadlines.

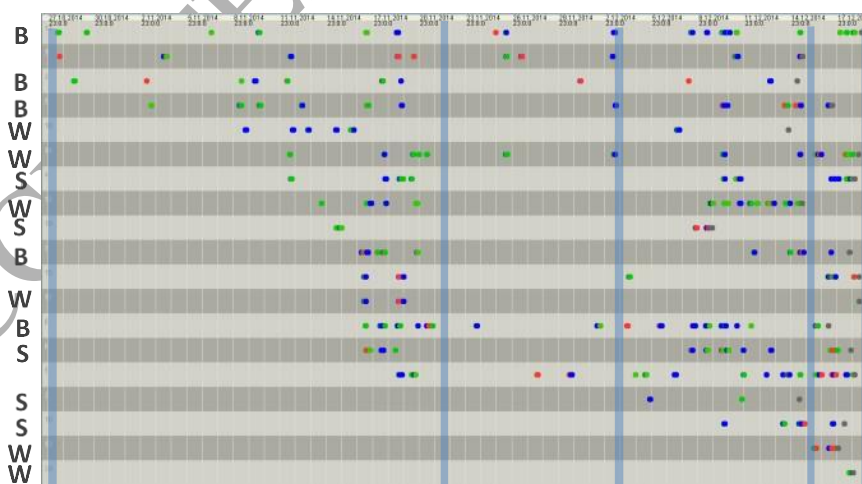


Figure 9. Sample comparison visualization to compare an engagement behavior of multiple learners (measured by frequencies of interactions, i.e. activities logged in a learning system for a specific learning task) with dotted chart technique (Sedrakyan et al., 2014).

Another example of comparison using aggregated data includes a clustered column visualization. Figure 10 shows a sample visualization comparing performance values of students with clustered distributions of scores accumulated per different learning tasks (stacked column chart on the left and a clustered column chart on the right). This visualization is recommended for comparing a few categories to avoid readability issues. A similar visualization is the stacked horizontal bar charts which is recommended when observation of time-related aspect is relevant. Figure 11 below shows an example of engagement comparison of different students measured by days accessed/used different learning resources.

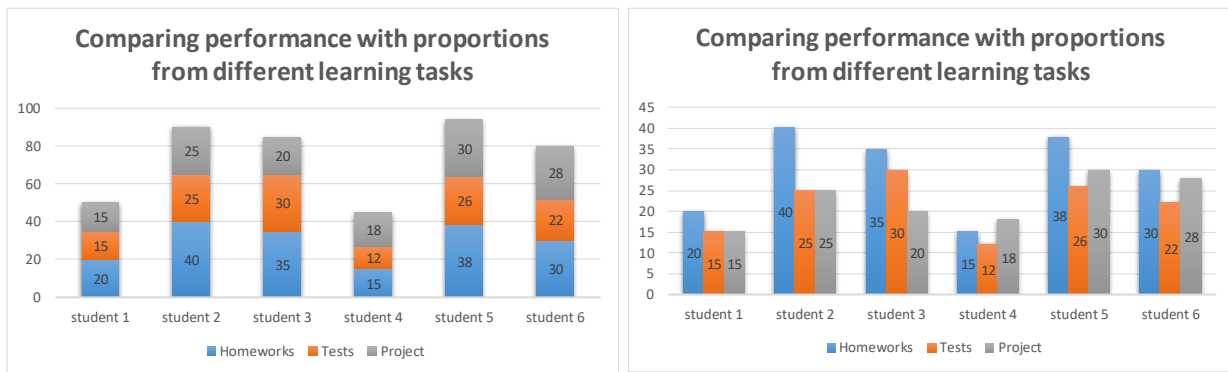


Figure 10. summative representation example showing performance score with proportions for different learning tasks for different learners for a planned period using a stacked column chart on the left and clustered column chart on the right.

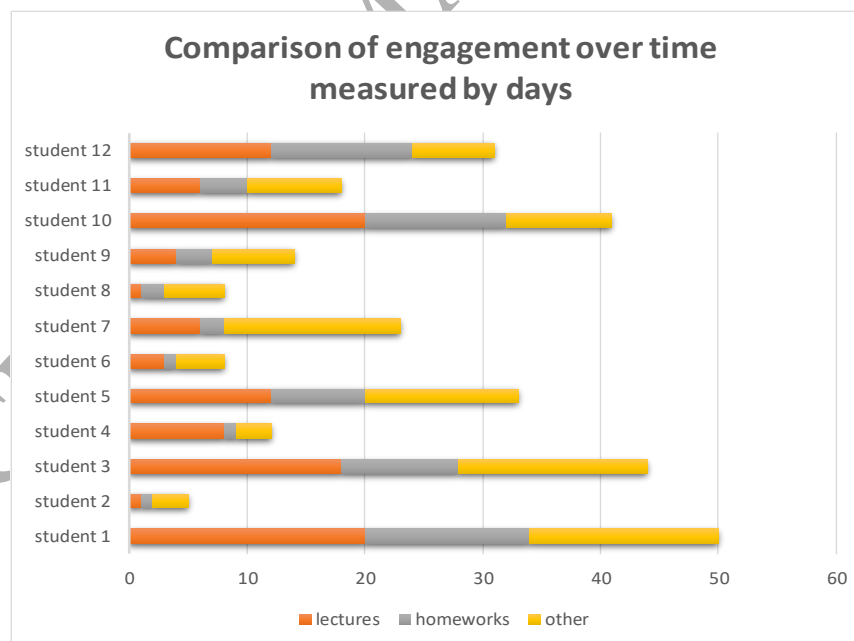


Figure 11. Aggregated summative representation example showing engagement of learners measured by days with proportions of devoted time to different learning tasks. The example makes use of clustered stacked bar chart.

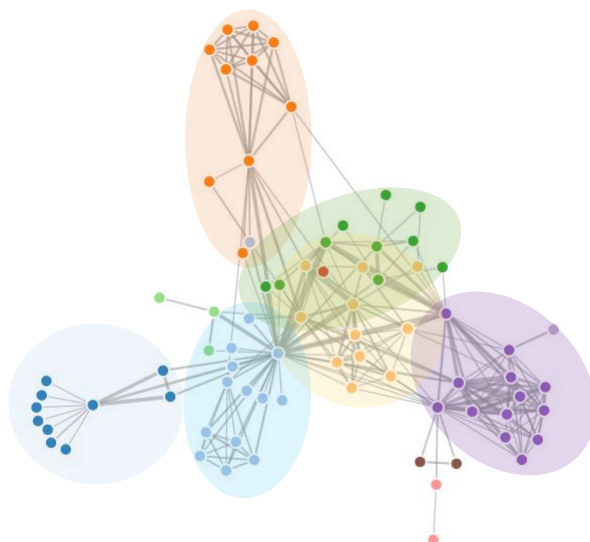


Figure 12. Sample network visualization using a force-directed graph visualization.

As learning processes are not limited to user interactions within learning environments, observing learner activities outside those environments will require additional visualization techniques. For instance, network analytics can be relevant when aiming to observe the most used technologies, devices, and software by learners and trying to derive insights on which of them can be associated with better learning outcomes. Similarly, a social network analysis, such as interaction patterns in social media can be explored with network analytics techniques. These analytics help to understand what the students may be doing throughout their day/week/month/semester and if patterns can be discovered from successful learners that others can learn from. A typical visualization for network analytics includes a force-directed graph (or a node graph) technique shown in Figure 12 in which relationships of different nodes can be observed (circled clusters). Such a visualization technique can be also used to visualize interaction within a learning environment that contains social interaction components, e.g., chat, forums, etc.

Sedrakyan et al. (2014, 2016, 2018) make use of process-discovery maps to visualize learning processes with the goal to detect process-oriented feedback needs during learning processes. An example includes a process map to observe a group interactivity for collaborative task-completion processes. The motivation for this choice is that group dynamics and interactivity are to a large extent predictive for the collaborative nature of learning processes. Such a visualization is relevant for behavioral aspects of learning where sequencing of activities is relevant as opposed to summative statistical representations (Sedrakyan, 2016). The use of process discovery maps has been successfully tested in various learning contexts for exploring an individual/group learning behavior and learning regulation, as well as interactivity within a group (Sedrakyan, 2016; Sedrakyan et al., 2014; Sedrakyan et al., 2016; Schoor & Bannert, 2012). Figure 13 shows interaction behavior of learners in a group based on user activities abstracted from activity logs within a learning environment (Sedrakyan et al., 2018), e.g., “ask,” “answer,” “comment,” “rate”, etc. The visualizations of activities (sequences and frequencies) suggest to a teacher if a satisfactory level of group dynamics has been reached depending on the intended interactivity level and learner roles.

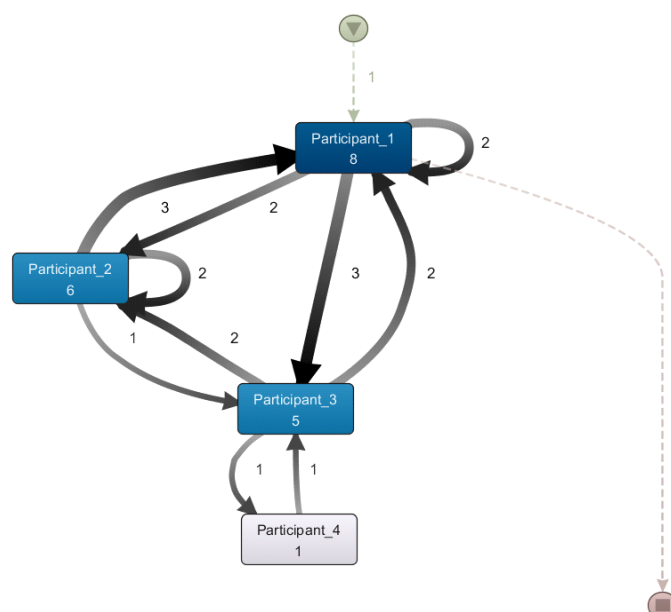


Figure 13. Sample visualization for tracking group interactivity with a process analytics approach (Sedrakyan et al., 2018).

Similarly, a process discovery map can be used for tracking an individual learner behavior for a specific learning task at different granularity levels. Sedrakyan et al. (2014) for example track learner behavior during a modeling task using learner activities within a modeling environment, such as “create”, “edit”, “delete”, “modify”, “simulate”, etc. that allows to detect behavior patterns associated with worse/better learning outcomes. In general, process discovery maps can be recommended for analysis of learning processes and learner behavior with the goal to identify process-oriented feedback needs as opposed to outcome-oriented feedback usually available when a learning task is completed (Sedrakyan, 2016). Such maps are in particular useful for identifying procedural errors, although they might indirectly also indicate cognitive (e.g., understanding related difficulties) during a learning process (Sedrakyan, 2016).

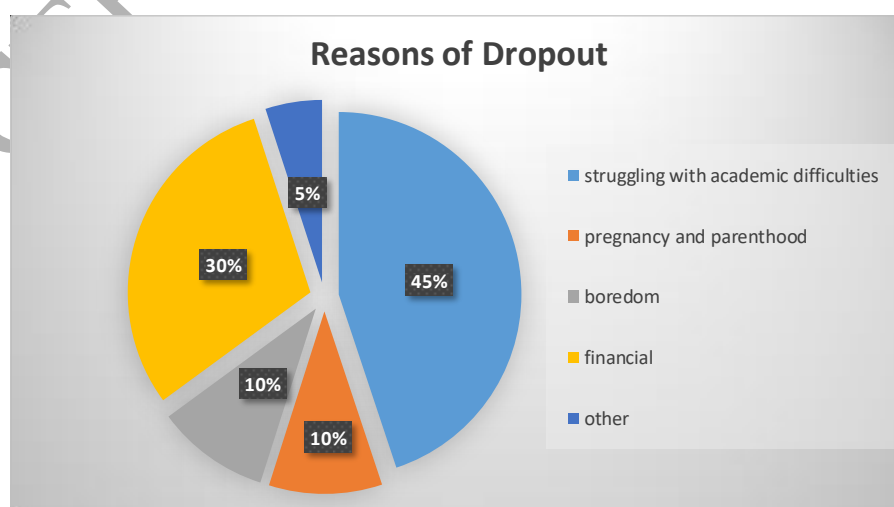


Figure 14. Sample visualization to represent a part-whole relationship (causes of dropouts in this specific case).

A pie-chart is used to visualize the proportions of a whole using numbers that ideally sum up to 100%. This chart is recommended to visualize a limited number of proportions to avoid readability issues. Figure 14 shows an example of visualizing the major four reasons of learner dropout while aggregating fewer common answers under “other reasons”.

Depending on the goal of interpretation and the stakeholder (e.g., an analyst may need a detailed representation while a teacher might need a high-level overview for a specific task without the need for exact proportions). Figure 15 shows an example of such high-level feedback (Martin & Ndoye, 2016) to a teacher in the form of word clouds². The goal of the visualization is to facilitate interactions with a large group of learners. In this specific example, a teacher assigned a hands-on exercise to students after a lecture to analyze the business requirements in the domain of banking represented in natural language and to derive relevant components (concepts, attributes, events, ...) for building a software model. The teacher wants to know if the lecture material was effectively understood (does the majority of students give correct answers?), but also whether there are major/minor difficulties (how many common wrong answers are provided?). Such an imperfect type of feedback will help to quickly analyze whether a specific part in a lecture needs to be focused further and what type of understanding difficulties need to be addressed both for a group of learners as well as individual students. The word cloud technique can be recommended for fast processing of learner feedback (e.g., surveys) where the goal is quick and approximate overview rather than perfect and detailed representations.

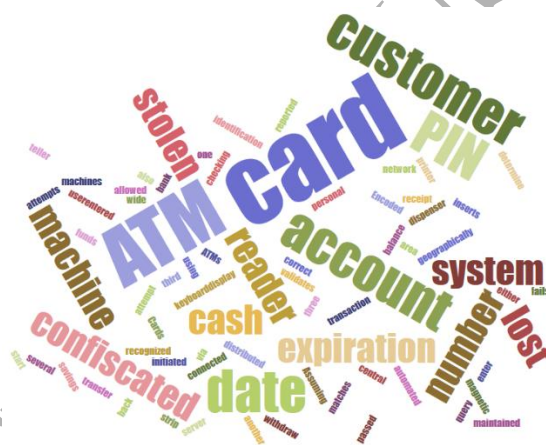


Figure 15. Quick high-level feedback visualization example using word cloud technique.

Among the typical visualizations for emotions are the spider charts using colored polar bars to show the frequencies of affective states for a given timeframe (see sample visualization shown in Figure 16). In another approach the affective states are visualized by means of a heat-map in which columns represent time units (e.g., days, weeks, or months) and rows represent students. Each affective dimension is represented by a cell, while the frequency level of each emotion is represented through the intensity of the cell color, e.g. the more intense the color, the higher the levels of the emotion is (see sample visualization shown in Figure 16). Leony et al. (2017) propose the visualizations both for learner and teacher-oriented dashboards.

² The word cloud example inspired from a course taught at KU Leuven. The page of the course can be found at: https://onderwijsaanbod.kuleuven.be/syllabi/e/D0I71AE.htm#activetab=doelstellingen_idm9009824

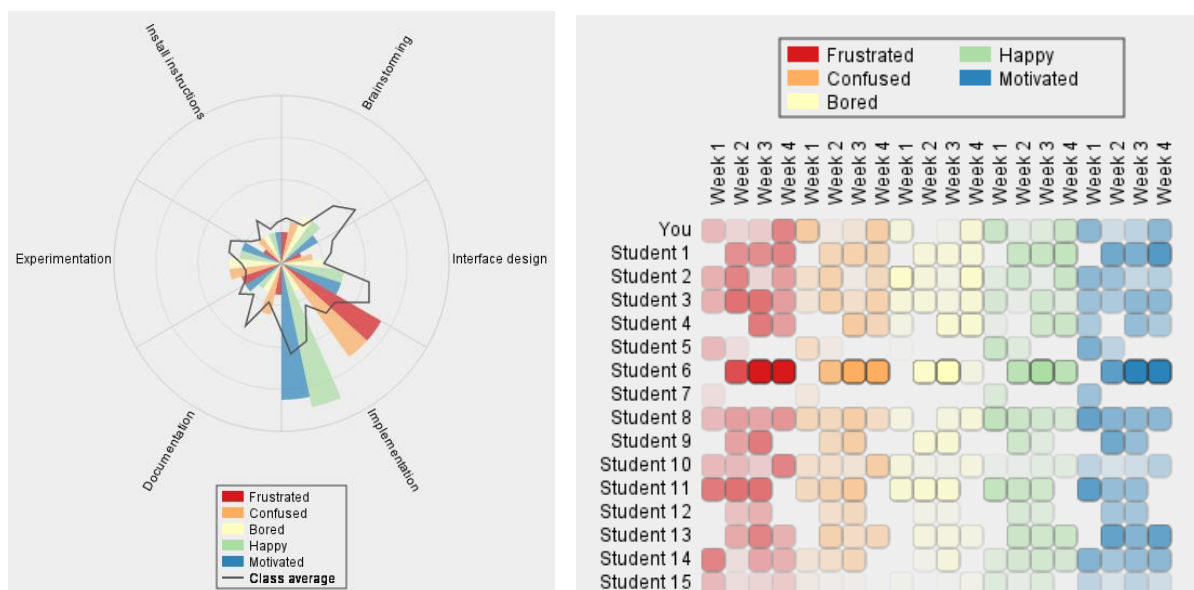


Figure 16. Sample affect state visualizations: radar chart comparing the levels of different emotions for a learner and class average (on the left), heat map showing the intensity of emotions over time linked to different learning task periods (on the right) – Leony et al. (2017).

In some cases, visualization of geospatial information, e.g., countries of origins of a learning group or registered learners for a specific MOOC is needed. In this case, a choice of a visual representation is rather straightforward, e.g., map/spatial plot visualization (see Figure 17). Color intensity can be used to compare the number of learners, e.g., the more intense is the color, the higher is the number of (engaged/registered/...) learners. The use of such maps is a relatively novel approach in the context of LADs (Vieira et al., 2018) and thus for each context relevant information and intended goals are to be defined. Such a visualization can for instance be used for different objectives such as distribution, comparison, and trends over time and may make use of different interactive techniques such as “zoom”, “filter”, “details-on-demand”, etc.

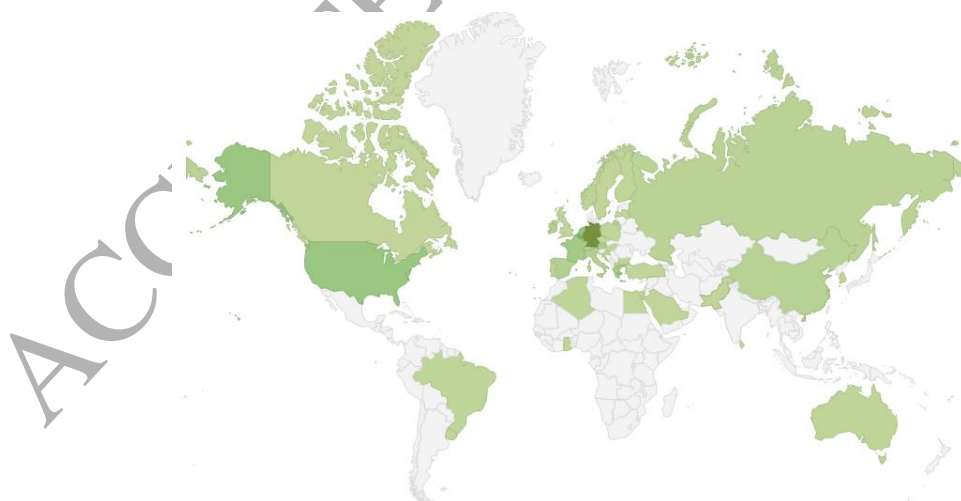


Figure 17. Sample map visualization to represent geospatial information for specified clusters of learners (engaged, registered, dropped, ...).

Scatter charts are used to compare relationships between two sets of values. Martin & Ndoeye (2016) demonstrate the use of a scatter plot visualization by comparing the relationships between time spent during a quiz and score obtained (see

Figure 18). Similarly, another dimension, such as number of times accessed, resources used, etc. can be considered. The authors further explain, that with such analysis an instructor can detect patterns and needs for further feedback (e.g., in this specific case students with below average scores were found to spend less than enough time on the task).

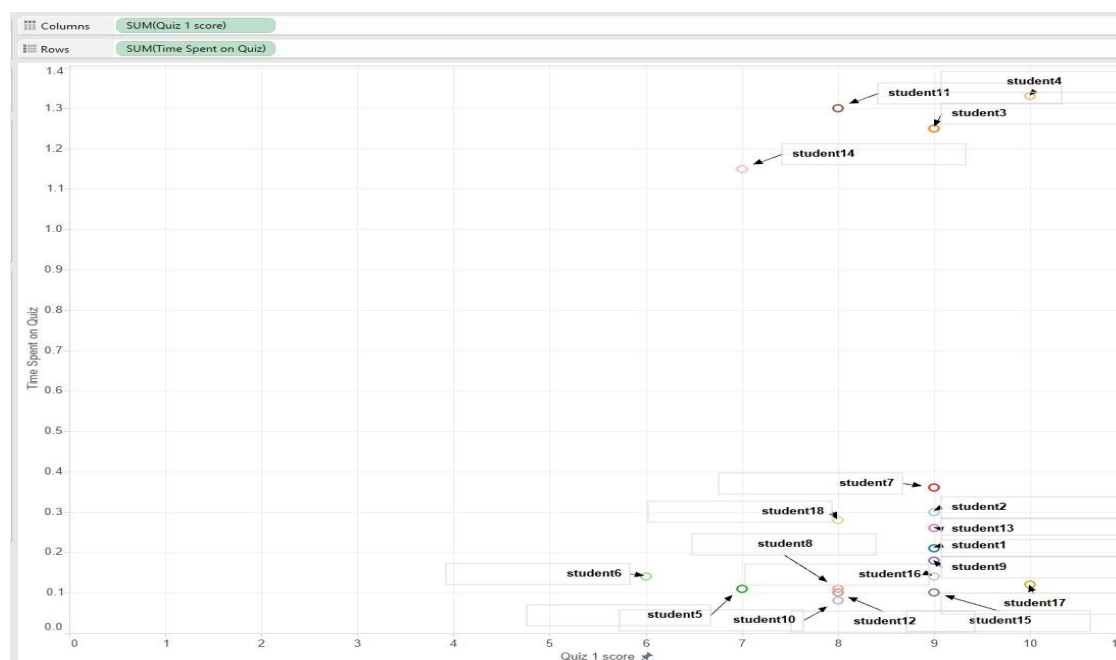


Figure 18. Scatter Plot depicting a quiz score and time spent (Martin & Ndoeye, 2016).

It may be needed to relate the values from one set with a range/interval of values from another set, such as intervals of time, ranges of scores, etc. Figure 19 shows an example of such variable representation by providing median values (Martin & Ndoeye, 2016) showing the median time spent on the quiz to be between 0.03 and 0.35 (hours), and the median quiz 1 score to be between 8 and 9 points.

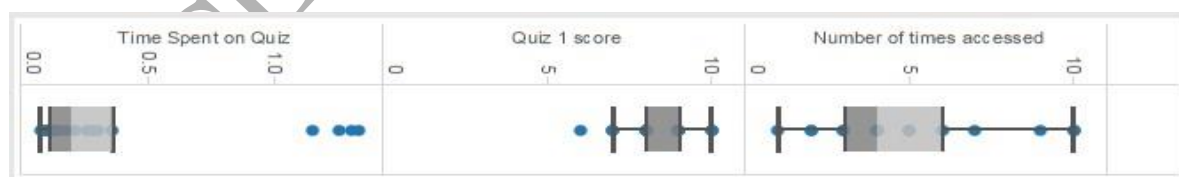


Figure 19. A sample range/intervals visualized as a box whisker plot (Martin & Ndoeye, 2016).

The examples presented in this paper are not exhaustive. To expand visualizations beyond the existing ones to support new contexts, a reader can be referred to visualization libraries for designing customizable visual representations, such as the D3-library³.

³ The source code to be found at: <https://github.com/d3/d3/wiki>

6.3. Scalable visualizations in the context of big data

While the concept of scalable visualizations for large datasets (e.g., MOOCs and wearable sensors by definition are big data technologies) is not the core topic of this work, nevertheless general recommendations can be discussed. One general rule of thumb is to keep visualizations at high abstraction levels and use interactivity and filters to zoom from high level visual views into more specific granular linked views, e.g., for different timeframes/learners, etc. A simple example could be a pagination for a large dataset represented with tabular visualizations to allow visualizations to deploy for a sliced dataset, while in a more advanced scenario one could use multi-dimensional data zooming into linked graphical representations. Another approach is to use distributed visualization systems each dealing with portions or distributed datasets for a same observable object. It has to be noted, however, that visualizing big data in the context of learning dashboards does not seem to offer a significant value since the human eye is not capable of identifying patterns on big data visualizations. While the choice of the tooling should be viewed in the context of explorative tasks mainly to assist research work, the real added value can be in the tasks such as data processing and aggregation. Hence, the main task in this context may be the use of powerful query engines, while the processed data can be visualized using traditional visualization techniques. Another topic that comes out of this discussion is the heterogeneity of data originating from various sources in different formats. A general recommendation could be using emergent big data technologies that enable harvesting/curation/fusion of such data for further processing by visualization engines (Sedrakyan, De Vocht, Alonso, Escalante, Orue-Echevarria, & Mannens, 2018) which constitutes a further research direction.

As big data is becoming a key topic, yet another relevant direction for future research concerns with visualizing real-time (live) data (e.g., sensors). A general rule of thumb is to show the capture of change over time (moving visualizations), optimized architectures and solutions are required to provide sustainable publishing/consuming of data (Rojas Meléndez, Sedrakyan, Colpaert, Vander Sande, Verborgh, 2018) in the context of LADs.

6.4. The role of subjective perceptions

Despite the intended goal, effectiveness, readability and other benefits of dashboard visualizations, user acceptance can be yet another important factor affecting the usability. Previous studies have identified important variables dealing with user acceptance for computer-assisted learning environments, such as the Technology Acceptance Model (Davis, 1989), which suggests ease of use and perceived usefulness as important factors contributing to the user acceptance (i.e., actual utility) of LAD feedback. Including built-in user feedback mechanisms will allow refining/improving/adjusting visualizations over time based on empirical evidence.

A number of personality models have been proposed to understand the individual characteristics and preferences (Tlili et al. 2016). Each one of these models is based on a different personality theory and presents different personality traits. Bayne (2004) claimed that the differences of the learners' personalities result in different ways of learners' engagement regardless of their personal interests or the degree of cognitive development. Previous studies also provide an overview of different personality models for the way user interfaces aspects (e.g., color and fonts) might impact (thus be useful) depending on the personality types (Tlili et al. 2016) which can be recommended for further refinement of visual representations in the context of dashboards. One possibility to adjust visual representation to user preferences is to allow highly interactive

dashboards with user controls that will allow personalization of visualizations (font, color, saturation, brightness, size, label, texture, shape, line curvation, spatial attribute, 2D/3D, ...).

6.5. Derived recommendations for the choice of LAD visualizations

Based on the analysis of earlier research on LADs design and feedback typology and visual paradigms, several guidelines can be recommended that exploit the relations between the discussed concepts in earlier sections. An overview of visualization recommendations is summarized in Table 4 below. The proposed mappings focus on dashboard design and educational science concepts discussed in the sections 3 and 4 from one side (column 1: Educational Concepts), and on the other side on their links with measurability concepts discussed in the context of LADs in section 3, such as observable artifacts in the context of backward design, profiling in the context of regulatory mechanisms underlying learning processes discussed in section 4, data characteristics/tasks (column 2: LAD design / data concepts), aims for visualizations (columns 3: Visualization concepts) which are discussed in section 5. Subsequently, possible visual representations are derived as general recommendations use of visualizations in the context of LADs (column 4: Recommended (possible) visual representations). The recommendations are derived based on the mappings between tasks, intended goals, aims for visualizations, and relevant visualization types discussed in section 5 as well as in the case example of section 6. The conceptual mappings can be suggested as a general map to guide the choice of visualizations when designing learner/teacher-oriented LADs.

Table 4 Overview of mapping LADs, data, visualization concepts and representations

Educational Concepts			LAD design / data concepts		Visualization concepts			Recommended (possible) visual representations
Intended goal / concept support	Dimensions		LAD concepts measurability	Data concepts (type/tasks)	Objectives	Reasons	Relevance	
Feedback	Cognitive types of feedback		outcomes of TSSGs	overview details-on-demand zoom	comparison	explore discover summarize (enjoy)	Learner / teacher	Bar- pie- charts (e.g. for comparative and summative overviews)
	Behavioral types of feedback (procedural)		learning goals optimal learning trajectory suggestions	relate (e.g., dependencies between pre-post- learning goals) tree	overview details-on-demand zoom in	Composition explore relate compare (enjoy)	Learner / teacher	Sequence, process map, flow chart, directed node graph
	Outcome-oriented	either cognitive or behavioral feedback on specific learning outcomes	outcomes of TSSGs	Same as for cognitive and behavioral feedback above	Same as for cognitive and behavioral feedback above	Same as for cognitive and behavioral feedback above (enjoy)	Learner / teacher	Bar- pie- area- charts (e.g. for comparative and summative overviews)
	Process-oriented	either cognitive or behavioral feedback on intermediate	(intermediate) outcomes of TSSGs or outcomes of intermediate	temporal overview zoom filter extract relate	trend over time with the focus on intermediate outcomes	explore discover compare (enjoy)	Learner / teacher	Bar- pie- area- line- charts, process/sequence/ discovery maps, time trend,

		e learning outcomes	TSSGs		and overall process			directed node graph
Regulated learning	Self-regulation	Self-oriented planning	Self-oriented profile	explore discover temporal Interactive relate (e.g., dependencies between pre-post- learning goals)	trend over time composition distribution	summarize present (enjoy)	Learner / teacher	Flow chart, sequence/process map, directed node graph
		Self-oriented monitoring	Self-oriented monitoring profile	overview zoom filter details-on-demand relate extract temporal	trend over time composition distribution	explore discover (enjoy)	Learner / teacher	(clustered / stacked) bar-column- chart, pie chart, line-chart area-chart, dotted chart, other trend-oriented plots
		Self-oriented adapting	Self-oriented adaptation profile	overview temporal relate	trend over time relationship	explore discover (enjoy)	Learner / teacher	Bar- line- area-charts, time trend-oriented plots (e.g. visualizing trial-error attempts and progress)
	Co-regulation	Peer-oriented planning	Peer-oriented planning profile	Interactive relate (e.g., dependencies between pre-/ post- learning goals with those of peers) zoom details-on-demand temporal network	relationship distribution trend over time composition	explore discover summarize present (enjoy)	Learner / teacher	Flow chart, sequence/process map, directed node graph
		Peer-oriented monitoring	Peer-oriented monitoring profile	overview zoom filter details-on-demand relate (e.g., with peers) extract temporal	comparison relationship trend over time composition	explore discover (enjoy)	Learner / teacher	(clustered / stacked) bar-combined parallel column- line- area –charts, dotted chart, other trend oriented plots
		Peer-oriented adapting	Peer-oriented adaptation profile	overview temporal relate (e.g., with own and peer outcomes)	trend over time relationship	explore discover (enjoy)	Learner / teacher	Bar- line- area-charts, time trend-oriented plots
	Socially shared regulation	Group-oriented planning	Group-oriented planning profile	shared interactive relate (e.g., dependencies between pre-/ post- learning goals) zoom details-on-demand temporal network	relationship distribution trend over time composition	explore discover summarize present (enjoy)	Learner / teacher	Flow chart, sequence/process map, directed node graph
		Group - oriented monitoring	Group-oriented monitoring profile	shared overview zoom filter details-on-demand relate (e.g., with group expectations) extract	Comparison (e.g., with own and group expectations) relationship trend over time composition	explore discover (enjoy)	Learner / teacher	radar- (clustered / stacked) bar-combined parallel column- line- area –charts, dotted chart, other trend oriented plots

				<i>temporal overview</i> <i>temporal relate (e.g., with own and group outcomes and expectations)</i>	<i>trend over time relationship</i>	<i>explore discover (enjoy)</i>	<i>Learner / teacher</i>	<i>Bar- line- area- charts, time trend oriented plots</i>
Learning goal orientation	<i>Mastery-orientation approach avoidance</i>	<i>Self-regulation</i>	<i>Self-oriented planning profile own performance on TSSGs</i>	<i>Same as for self-regulation with the focus on mastery level thresholds</i>	<i>Same as for self-regulation with the focus on mastery level thresholds</i>	<i>Same as for self-regulation with the focus on mastery level thresholds (enjoy)</i>	<i>Learner / teacher</i>	<i>Flow chart, sequence/process map, directed node graph, any form of visualization that allows further comparative views for achievement</i>
	<i>Performance-orientation approach avoidance</i>	<i>Self- Co- Socially shared regulation</i>	<i>Self-/Peer-/Group oriented planning profile Self-/Peer-/Group-performance on TSSGs</i>	<i>Same as for Self- Co- Socially shared regulation with the focus on summative representations and comparisons with peers/group performance</i>	<i>Same as for Self- Co- Socially shared regulation with the focus on summative representations and comparisons with peers/group performance</i>	<i>Same as for Self- Co- Socially shared regulation with the focus on summative representations and comparisons with peers/group performance (enjoy)</i>	<i>Learner / teacher</i>	<i>Flow chart, sequence/process map, directed node graph, any form of visualization that allows parallel comparative views for achievement</i>
Effectiveness of learning	<i>Accuracy</i>		<i>outcomes of TSSGs or outcomes of intermediate TSSGs</i>	<i>overview zoom filter details-on-demand relate</i>	<i>Comparison relationship composition</i>	<i>Explore Discover Summarize present (enjoy)</i>	<i>Learner / teacher</i>	<i>any form of visualization that allows interactive comparative views for achievement</i>
	<i>Completeness</i>		<i>outcomes of TSSGs or outcomes of intermediate TSSGs</i>	<i>overview</i>	<i>comparison relationship distribution composition</i>	<i>explore discover summarize present (enjoy)</i>	<i>Learner / teacher</i>	<i>any form of visualization that allows further comparative views for achievement</i>
Efficiency of learning	<i>Effort</i>		<i>resources time spent on TSSGs</i>	<i>overview relate extract temporal</i>	<i>comparison relationship distribution trend over time composition</i>	<i>explore discover summarize present (enjoy)</i>	<i>Learner / teacher</i>	<i>any form of visualization that allows comparative views for achievement, resource usage and time trend e.g. column- line- charts</i>
User preferences	<i>User feedback</i>			<i>overview filter details-on-demand relate</i>	<i>comparison relationship distribution composition</i>	<i>explore discover summarize enjoy</i>	<i>teacher</i>	<i>Word clouds, column- pie- charts</i>
	<i>User control</i>			<i>Interactivity filter zoom details-on-demand</i>	<i>-</i>	<i>-</i>	<i>Learner / teacher</i>	<i>Any form of visualization that allows interaction with the purpose to customize visualization and affect feedback e.g. receive time detail</i>

Emotion regulation	Support for awareness of affective states	affect intensity for a TSSG /timeframe compared with those of peers	overview zoom filter relate extract temporal	comparison relationship distribution trend over time composition	explore discover summarize present (enjoy)	Learner / teacher	Heat map, radar charts (e.g. to show intensity level), trend line, column- pie- bar- charts (e.g. comparative overviews)
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It has to be noted that the recommendations above are not be considered exhaustive but rather to suggest possible visual representations in the context of LADs design based on understanding of relevant educational and visualization paradigm concepts and their relationships. The proposed concepts are not mutually exclusive. Often different combinations might be needed depending on different learning contexts and needs. As already mentioned in earlier sections, behavioral feedback can, for instance, be supported by cognitive types of feedback that focus on intermediate learning outcomes, while a process-oriented feedback can use a combination of a cognitive and behavioral feedback that may use outcome-oriented feedback to intermediate outcomes of a learning task, etc.

7. Conclusion

In this work we propose general recommendations for selecting visualization representations for learning dashboards based on conceptual mapping between visualization paradigms and dashboard design concepts found in earlier research. The list of visual representation examples is not exhaustive as the examples are used to illustrate possible visualizations that consider certain characteristics such as targeted goal, audience, data structure, links to learning science perspective. The work contributes to the domain of visualizations by mapping the intrinsic characteristics of learning data and the aims for interpretation specifically for the learning domain. The work also contributes to the domains of learning analytics and learning dashboards by proposing a visualization framework (conceptual mappings) to support learning analytics data visualization and in the context of designing learning dashboards. While we propose a general guidance based on conceptual mappings, empirical studies are further recommended to study the effectiveness of the proposed visualizations framework with real experiences using a prototypic solution. This will allow to further refine the specific needs for each concrete visualization (such as detailed design specifications) for specific learning contexts as well as explore personalization aspects. Thus, possible future work will be directed towards (1) an empirical evaluation of the proposed framework, (2) the deployment of a prototype that allows automating the recommendations for the choice of visualization concepts/plots based on targeted goals and typologies of feedback provided as input parameters and/or automation of extraction of such parameters from the datasets at hand. Yet, other possible directions for future work include (3) expanding the scope of visualizations to include personality models, interaction paradigms and user controls towards personalization of visualizations as personality can affect the way a learner interacts within learning environments or perceives visual components, (4) enjoyable elements in the context of gamified learning environments as well as (5) considering biofeedback perspectives that use physiological data collected from wearable sensors. Visualization of multi-modal data collected from various wearable devices using big data oriented scalable approaches can be yet another future work direction in this domain.

The work can also be expanded to include more granular level recommendations for designing visual representations as well as automated support for generating such recommendations for each concrete case and context, e.g., based on the selection of data type, goals, etc., and, in fact, to support automated generation of such visualizations in the future.

8. Acknowledgments

This work was supported by Internal Funds of KU Leuven - PROFEELEARN PDM/16/044

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